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A memetic algorithm for a relocation-routing problem in green production of gas considering uncertainties

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ABSTRACT

This study introduces a relocation-routing problem with a fuzzy amount of sewage and stochastic travel time in natural gas production. In this study, a set of sewage treatment plants (STPs) and a certain number of gas-gathering stations (GGSs) are distributed on the field. With the increasing amount of production, however, the current STPs cannot satisfy the production level. Policymakers propose several location candidates to build new STPs and aim to minimize the total cost of running the newly built STPs and the original STPs. The practical attributes of the sewage return logistics, capacity of vehicles and STPs, uncertain amount of sewage, stochastic travel times, and other constraints are taken into account. The new problem proposed in this study is defined as Relocation-Routing Problem with Fuzzy Sewage and Stochastic Travel Time (RLRPFSSTT), which has never been investigated before. To minimize the total cost, including the construction cost of newly opened STPs and transportation cost between STPs and GGSs, this paper designs a memetic algorithm to optimize location and routing problems simultaneously. Benchmark-based experimental data is designed, and the computational results demonstrate the effectiveness of the proposed memetic algorithm. Sensitivity analysis and comparisons are also carried out to validate the advantage of considering uncertainties. The proposed model and algorithm are meant to further supplement and extend the location and routing models, as well as have great significance for the decision-makers of industrial logistics in oil fields and coal mines.

1. Introduction

During the past decade, the logistics industry has witnessed extraordinary growth. Stępień et al. [1] disclosed that the transportation cost had accounted for a significant part of the logistics cost. Notably, this value in developing countries, such as China, was about 70% to 90% [2]. Therefore, the optimization of material transportation and distribution is of great significance for reducing logistics costs, as well as improving the operational efficiency of enterprises.

A local gas enterprise, abbreviated LGE (Considering privacy, we are not convenient to disclose the name of the enterprise here. This article uses LGE to indicate the name of the company), has many gas-gathering stations (GGSs) and sewage treatment plants (STPs). Usually, LGE is located in a remote area with complex geomorphology. In each GGS, sewage, including condensate and methanol, is frequently generated daily during the pipe network operation in the production. These sewage need to be transported to the STPs for purification and separation, thereby refining useful substances such as condensate and methanol. With the expansion of each GGS's production scale, the throughput of the original purification plant cannot meet the production requirements. To deal with this situation, policymakers proposed several candidate locations for building new STPs and aimed to minimize the total cost of running the newly built STPs and original STP.

The STP relocation problem is an extended version of facility location problem (FLP), which is a medium-term or a long-term decision-making of enterprises depending on the problems and has vital strategic significance for the development of enterprise's logistics. However, rerouting problem is a variation of VRP, which is a short-term or a medium-term decision-making process for enterprises and has a crucial tactical reference value for logistics distribution for enterprises. From the logistics in practice, FLP and the VRP have much intrinsic relevance

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Nomenclature

FLP	facility location problem
VRP	vehicle routing problem
LRP	location routing problem
RLRP	relocation routing problem
LGE	a local gas enterprise
STP	sewage treatment plant
GGS	gas-gathering station.
DPI	dispatcher preference index
API	assignment preference index
Cd	cost of the depots
Cr	cost of the routes

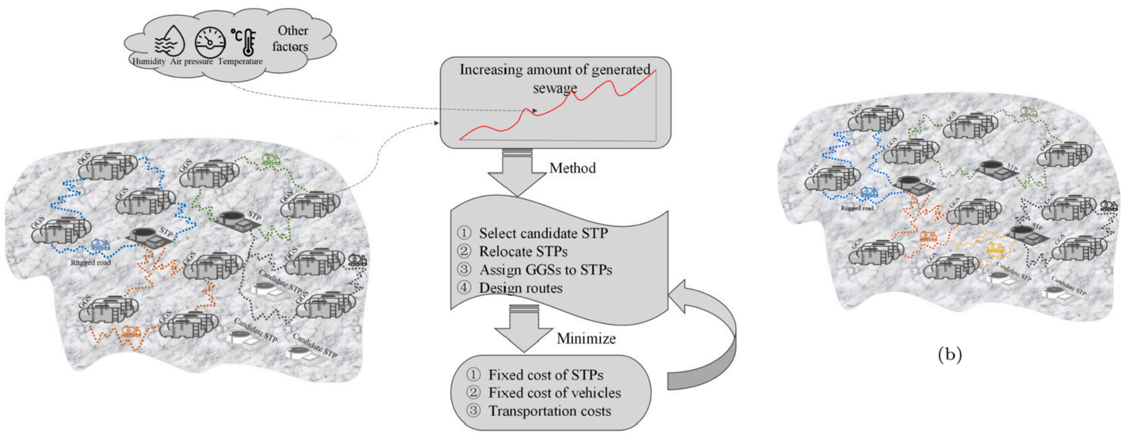


Fig. 1. An overview of the studied problem.

in the decision-making process: both should generally consider the distribution of materials distribution centers and gas-gathering stations (GGSs).

The procedures of identifying the final location of the STPs can be listed as follows: Firstly, the policy-makers need to provide a few candidate locations for constructing STPs by evaluating the relevant conditions, including land accessibility and environmental factors. Secondly, the specific opened facilities should be selected. The goal is to construct STPs with minimizing the total costs, including the construction cost of STPs, and transportation cost between STPs and GGSs by considering the uncertain capacity of STPs and uncertain transportation time between STPs and GGSs. From the practice of the GGS, observed that the amount of generated sewage (AGS) is not a deterministic value each day. Actually, the AGS has a great relationship with the daily temperature, humidity, air pressure, the actual amount of gas production and other complex factors. So, it is unpredictable even by some experienced workers. Additionally, the gas filed is located in mountainous maybe with complex terrain. In these areas, the travel time between each arc is non-deterministic due to the rugged road, changeable and inclement weather. So, it is of great significance to consider these uncertainties when modeling our problem [3,4]. It is of great importance to integrate the two issues simultaneously, which was defined as location routing problem (LRP) [5]. This paper studies the STP relocation problem and rerouting problem considering the uncertainties of amount of AGS and travel time, which has never been investigated before. Fig. 1 gives an overview of the studied problem. Fig. 1a presents the current situation faced by a LGE and the proposed solution method. Fig. 1b gives a solution scenario after applying the proposed solution method.

The main contributions of this study are summarized as follows:

(1) A relocation-routing problem in the field of green production of natural gas is studied and this problem is originally from real engineering applications.
(2) To overcome the intractability of handling uncertainties considered in the optimization model, we transfer the constraints related to fuzzy and stochastic information to the handleable constraints, which could be directly used in the meta-heuristics (memetic algorithm).
(3) Since the studied problem is computationally challenging, this study employees a memetic algorithm to solve the proposed optimization problem.
(4) Stochastic simulation and memetic algorithms are integrated to solve the studied problem by minimizing the total cost, and sensitivity analysis is also performed to help the policy-makers make a reasonable decision.
(5) Benchmark based instances are introduced and the experimental results demonstrate the effectiveness and efficiency of the proposed memetic algorithm, as well as the advantage of considering uncertainties in the model.

The remainder of the paper is organized as follows. Section 2 analyzes the relevant literature. The mathematical formulation and memetic algorithm are presented in Sections 3 and 4, respectively. Computational experiments are given and analyzed in Section 5. Finally, the conclusions and future studies are presented in the Section 6.

2. Literature review

Considering that the studied problem is regarded as a further extension of the classical location-routing problem with considering the uncertainties. The literature review section is composed of four categories. First, the recent works on VRP and scheduling are discussed, then recent works about LRP are investigated. After that, the recent works on routing and scheduling problems with uncertainties are presented. Finally, we discuss the related work with the memetic algorithm, which is the main methodology in this study.

2.1. Vehicle routing and scheduling problem

Capacitated vehicle routing problem (CVRP), which could be regarded as a multi-traveling salesman problem problem with

Table 1
Recent research related to fuzzy variables and optimization.

Authors	Studied problem	Solving approach
Cao and Lai [16]	Open vehicle routing problem	Differential Evolution
Zarandi et al. [17]	Capacitated Location-routing problem	Simulated Annealing
Sadeghi et al. [18]	Hybrid vendor-managed inventory and transportation problem	PSO
Sarkar and Mahapatra [19]	Fuzzy inventory model	Heuristic algorithm
Berrichi et al. [20]	Joint Integration of Production Schedule and Maintenance Planning	Multi-objective GA
Bahri et al. [21]	Multi-objective VRP	Scalable algorithms
Sun et al. [22]	flexible job shop scheduling	hybrid cooperative co-evolution algorithm
Sun [23]	Road–Rail intermodal routing problem	branch-and-bound algorithm
Gupta et al. [24]	green vehicle routing problem	discrete fuzzy-hybridised GA
Li et al. [25]	flexible job shop scheduling	Self-adaptive multi-objective evolutionary algorithm

considering the capacitated constraints, was first proposed and defined by Dantzig and Ramser [6] and it is one of the most basic and representative models in the family of VRPs. The algorithms for solving VRP are divide into two classes: namely exact algorithms and heuristic algorithms. Exact algorithms mainly include Dynamic Programming, Branch and Bound, and Lagrangian relaxation, column generation etc. Meta-heuristic algorithms obtain the solution through the global search method and can temporarily accept the poor solution that appears in the search process. Meta-heuristic algorithms will improve the solution itself in the specific application process and make the final solution close to the optimal solution as much as possible. Common meta-heuristic algorithms have been applied to solve the classical VRP problem. These meta-heuristics include Genetic Algorithm, Simulated Annealing Algorithm, Tabu Search Algorithm implemented by, Particle Swarm Optimization, Ant Colony Algorithm etc.. Additionally, nesting and mixed algorithms are designed to improve the solution of the instances further.

Han et al. [7] studied the job shop scheduling problem with taking into account minimizing the economic cost and the energy consumption. In this work, a multi-objective optimization is constructed, and to solve the model, the authors designed a discrete evolutionary algorithm. Qin et al. [8] investigated a blocking flow shop scheduling problem with taking into account the energy consumption criteria. In order to solve the model, a modified iterated greedy local search is proposed. Experimental results for 140 benchmark instances have been reported, and the comparison performed with the state-of-the-art highlight the efficiency of the improved algorithm.

2.2. Location routing problem

LRP is also an NP-hard problem, which can be viewed as the combination of FLP and VRP. When the size of clients and facilities are slightly larger, traditional exact algorithms (such as linear programming, branch and bound method, cutting plane method, and dynamic programming method) tend to be powerless. The meta-heuristic algorithms are the most commonly used approach to obtain a satisfactory solution. In an attempt to find a better solution or lower bound for LRP, many works [9–11] developed heuristics based on the attributes of the problem. Especially, Prins et al. [10] proposed a two-phase approach to solve the LRP problem. In the first phase, the routes and their customers are grouped into super-clients, which poses a problem of location of the facilities, which is then resolved by Lagrangian relaxation of the assignment constraints. In the second phase, routes from the resulting multi-destination VRP are enhanced using a granular tabular search heuristic.

2.3. Routing and scheduling problem with uncertainties

In the real practice of routing and scheduling problem, many factors such as customer's demand, travel time, etc. are not always deterministic. If we ignore these uncertainties when modeling the problem, the optimal solution obtained may be not reasonable enough when apply into practice. Fuzzy theory and stochastic probability provide effective tool for describing uncertainties. In the past 10 years, many researchers have introduced fuzzy theory into FLP [12], LRP [13], and Vehicle Routing Problem [14]. Afsar et al. [15] proposed a multi-objective optimization model to solve the job shop scheduling problem with taking into account the uncertain times. More applications, in recent years, are summarized in Table 1. However, compared with the classical LRP and its extension, the relocation-routing problem is less investigated.

2.4. Memetic algorithms

On the basis of the genetic algorithm that simulates the biological evolution process, Moscato and Cotta [26] proposed a memetic algorithm (MA) that simulates the cultural evolution process. MA is regarded as one of the most powerful population-based evolutionary algorithms, and a comprehensive survey of MA was conducted by Chen et al. [27], Neri and Cotta [28], Krasnogor and Smith [29].

Some early results about MA for routing problems are reported by Prins and Bouchenoua [30]. Labadi et al. [31] made the earliest attempt to design MA for solving the vehicle routing problem and time window. The main structure of MA is composed of the basic genetic algorithm and the local search operators, which provides a learning strategy for an individual in the genetic algorithm. Experimental results on the 56 classical benchmark instances [32] demonstrated that the designed MA is efficient. Ngueveu et al. [33] proposed a MA for solving the classical cumulative capacitated vehicle routing problem (CCVRP), which considered minimizing the sum of the arrival time at customers. This work presented the lower bound and upper bound of the CCVRP. Specifically, the upper bound was obtained by the proposed MA. Nagata et al. [34] investigated the solving approach of VRPTW by introducing a new MA, which is composed of a new operator: existing edge assembly crossover. Additionally, they proposed a novel penalty-based function to eliminate capacity and time windows violations. The intensive experimental results demonstrated that their algorithm could reach remarkable results compared with the published results. Mendoza et al. [35] proposed the results for solving the vehicle routing problem with stochastic demand.

Wang et al. [36] studied the multi-objective periodic VRPTW by proposing a MA. Meanwhile, Wang and Lu [37] investigated a MA for solving the competition for a green CVRP. García-Ródenas et al. [38] integrated MA and gravitational search algorithm to train the feedforward neural networks, and simulation results showed that the proposed framework works well.

Many researchers regarded MAs as hybrid genetic algorithms or genetic local search. In fact, MAs provide a framework or a concept. Under this framework, different search strategies are used. Dengiz et al. [39] investigated the communication network topologies optimization problem by designing a hybrid genetic algorithm and local search with specialized encoding and initialization. Asadzadeh [40] implemented a local search genetic algorithm to solve the job shop scheduling problem with agents.

Compared with the analysis above, we conclude the following two points.

Table 2
Notations in the mathematical model.

Notations	Descriptions
OS	set of the original existing STP.
N	set of GGS;
CS	the set of candidates of STPs.
$F = OS \cup CS$	set of STP.
$N_0 = F \cup N$	set of all the vertices, including STPs and GGSs;
K	set of the vehicles.
v_{ij}	average driving speed during GGSs i and j
w	the price for a unit distance.
$C = (i,j) : i,j \in N$	transportation cost matrix, and each element $c_{i,j} = w * t^{\xi}_{ijk} v_{ij}$
CF_i	fixed cost of STP i
CV_k	fixed cost of vehicle k
SC_i	capacity of STP i
VC_k	capacity of vehicle k;
$\widetilde{d}_i = [d_{i1}, d_{i2}, d_{i,3}]$	fuzzy AGS of GGS i
TL_i	loading time for the sewage at GGS i
DPI	dispatcher preference index
API	assignment preference index
t^{ξ}_{ijk}	travel time on arc (i,j) in route k in the scenario ξ
AC	additional cost generated by the failure route in an uncertain environment
PC	planned cost for a specific solution in an uncertain environment
TC	total cost for a given solution in an uncertain environment

- (1) Despite the abundant studies about LRP, the current works are aimed at helping companies plan a completely new logistics layout. In developing countries, such as China, many companies are facing business expansion. This means that the most primitive logistics layout cannot meet the growing development needs. Therefore, it is necessary to optimize further and add new logistics facilities on the basis of the original logistics facility layout to keep the entire logistics system in an optimal state. Therefore, this research is an essential reference value for making up for the existing deficiencies and providing logistics decision-making for developing enterprises.
- (2) Despite the abundant investigations considering uncertainties in their models, few of them considers the fuzzy variables and stochastic variables simultaneously. This work derives the formulations of AGS under fuzzy chance constrained programming, and designs a reasonable chromosome structure. Then the complex constraints are incorporated into the MA to obtain an approximate optimal solution of the problem.

To sum up, our work formulates an relocation-routing problem with considering fuzzy AGS and stochastic travel time, then MA based heuristic is developed to solve this issue. Finally, experimental results show the advantage of viewing the uncertainties when modeling the problem.

3. Problem formulation

This section gives details about the mathematical formulation of the studied problem. The description of fuzzy AGS is given in Section 3.1, then the assumption and the fuzzy chance programming are presented in Section 3.2. Finally, the important constraints related to fuzzy demand and stochastic travel time are clarified in Sections 3.3 and 3.4, respectively.

3.1. Fuzzy AGS

In this section, the theory of fuzzy credibility [41] is employed to describe the uncertain variables of AGS. Let us consider the triangle fuzzy variable $\widetilde{d}_i = (d_{i,1}, d_{i,2}, d_{i,3})$ as the AGS of a given GGS i, the detailed introduction about $\widetilde{d}_i$ is shown in the supplementary material. Let r be a deterministic parameter. Let $Cr(\cdot)$ be the credibility operator, we can derive the formulation (1) to calculate the chance that the event $\widetilde{d} \geq r$ happens [3,41].

$$Cr\{\widetilde{d} \geq r\} = \begin{cases} 1, & \text{if } r \leq d_1; \\ \dfrac{2d_2 - d_1 - r}{2(d_2 - d_1)}, & \text{if } d_1 \leq r \leq d_2; \\ \dfrac{d_3 - r}{2(d_3 - d_2)}, & \text{if } d_2 \leq r \leq d_3 \\ 0, & \text{if } r \geq d_3; \end{cases} \tag{1}$$

3.2. Assumptions and model

The assumptions of the model are itemized as follows.

- The vehicles are homogeneous, i.e., each vehicle has an identical maximum speed, loading capacity, and empty vehicle weight.
- Each vehicle starts from the STP.
- Each vehicle cannot be used more than once.
- The AGS of each GGS i is a triangle fuzzy variable which can be described as $\widetilde{d}_i = (d_{1,i}, d_{2,i}, d_{3,i})$.
- The transportation cost between ith GGS and jth GGS is c_{ij}.
- Each driver carries out one route in the process of loading sewage; in case that remaining capacity is not sufficient for the next GGS, he/she must return to the STP, and unload all the sewage of vehicle, then continues serving the remaining GGSs on the road (task list).

The studied problem in our work defined on a complete, weighted and undirected network (N_0, E, C). The detailed notations are explained in Table 2.

Decision variables are described as follows.

$$x_{ijk} = \begin{cases} 1 & \text{if the } k\text{th vehicle travels from GGS } i \text{ to GGS } j, \forall i,j \in N_0; \\ 0 & \text{otherwise.} \end{cases}$$

$$y_n = \begin{cases} 1 & \text{if the } n\text{th candiate is selected to build the STP, } \forall n \in F; \\ 0 & \text{otherwise.} \end{cases}$$

$$z_{in} = \begin{cases} 1 & \text{if the } n\text{th GGS is assigned to STP } n, \forall i \in F, \forall n \in N; \\ 0 & \text{otherwise.} \end{cases}$$

$$\min z = \sum_{k\in K}\sum_{i\in N_0}\sum_{j\in N_0} c_{ij}x_{ijk} + \sum_{n\in F} CF_n y_n + \sum_{i\in F}\sum_{j\in N}\sum_{k\in K} CV_k x_{ijk} + AC \tag{2}$$

subject to

$$\sum_{k\in K}\sum_{j\in N_0} x_{ijk} = 1, \forall i \in N \tag{3}$$

$$Cr\left(\sum_{j\in N}\sum_{i\in N_0} \widetilde{d}_j x_{ijk} - VC_k \leq 0\right) \geq DPI, \forall k \in K \tag{4}$$

$$\sum_{j\in N_0} x_{ijk} - \sum_{j\in N_0} x_{jik} = 0, \forall i \in N, k \in K; \tag{5}$$

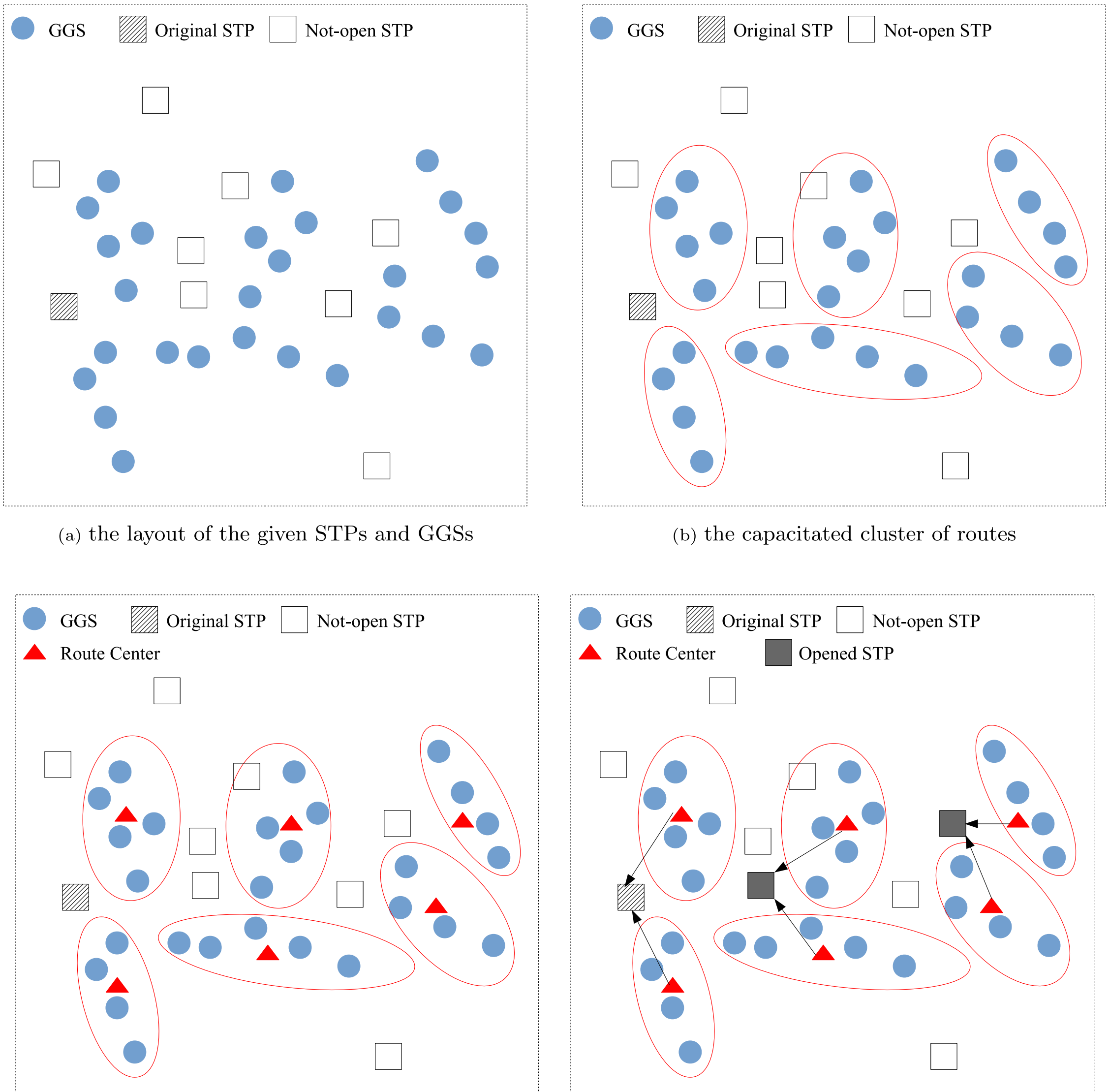
$$\sum_{i\in F}\sum_{j\in N} x_{ijk} \leq 1, \forall k \in K; \tag{6}$$

$$\sum_{i\in S}\sum_{j\in S} x_{ijk} \leq |S| - 1, \forall S \subseteq N, k \in K \tag{7}$$

$$\sum_{u\in N} x_{iuk} + \sum_{u\in N, u\neq j} x_{ujk} \leq 1 + z_{ij}, \forall i \in N, j \in N, k \in K; \tag{8}$$

$$Cr\left(\sum_{j\in N} d_j z_{ij} - SC_i y_i \leq 0\right) \geq API, \forall i \in F. \tag{9}$$

$$P\left(\sum_{i\in N_0}\sum_{j\in N_0} t^{\xi}_{ijk} \leq B\right) \geq \alpha \tag{10}$$



(a) the layout of the given STPs and GGSs

(b) the capacitated cluster of routes

(c) the centers of routes

(d) assign routes to STP

Fig. 2. The main procedures for generating initial solutions.

<table>
<tr><td colspan="11">Chromosome</td></tr>
<tr><td colspan="4">Segment 1</td><td colspan="4">Segment 2</td><td colspan="3">Segment 3</td></tr>
<tr><td>Gene</td><td>Gene</td><td>Gene</td><td>Gene</td><td>Gene</td><td>Gene</td><td>Gene</td><td>Gene</td><td>Gene</td><td>Gene</td><td>Gene</td></tr>
<tr><td colspan="4">GGS index</td><td colspan="4">VRP routes</td><td colspan="3">STP index</td></tr>
<tr><td colspan="4">m bit</td><td colspan="4">m bit</td><td colspan="3">k bit</td></tr>
</table>

Fig. 3. Chromosome design.

$$y_i = 1; \forall i \in OS; \tag{11}$$

$$x_{ijk} \in \{0, 1\}, \forall i \in N, j \in N, k \in K; \tag{12}$$

$$y_i \in \{0, 1\}, \forall i \in F; \tag{13}$$

$$z_{ij} \in \{0, 1\}, \forall i \in F, j \in N; \tag{14}$$

The objective function (2) aims to minimize all the costs, including transportation cost, the fixed cost of the vehicles and STPs, as well as the additional cost of AC caused by failure route in the fuzzy environment. Here we should emphasize that the approach of calculating AC can be

Chromosome

Segment	1	2	3
Gene	1 2 1 4 4 2 3 2 4 4 1 4 4 3 3	10 11 12 2 15 3 8 4 14 9 1 13 5 7 6	3 1 1 3
Map	↕ ↕ ↕ ↕ ↕ ↕ ↕ ↕ ↕ ↕ ↕ ↕ ↕ ↕ ↕	↕ ↕ ↕ ↕ ↕ ↕ ↕ ↕ ↕ ↕ ↕ ↕ ↕ ↕ ↕	↕ ↕ ↕ ↕
Index	1 2 3 4 5 6 7 8 9 10 11 12 13 14 15	4 1 4 2 3 1 2 4 3 4 1 4 4 3 2	1 2 3 4
Meaning	Assignment of vehicles and GGSs	Visiting order of the GGSs in vehicles	assignment of vehicles and STPs

*In the gene row, the green font denotes the index for GGS. The red font represents the index for vehicle and the blue font represents the index for STP.

Fig. 4. Example of chromosome encoding .

ID of STP	No. of Vehicle	Serviced GGS
3	1	1, 3, 11
1	2	2, 6, 8
1	3	7, 14, 15
3	4	4, 5, 9, 10, 12, 13

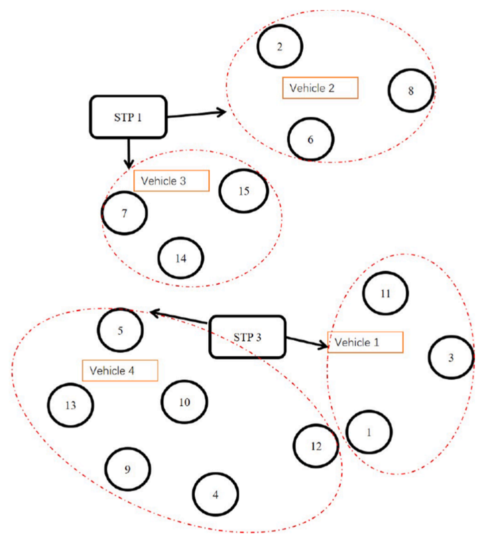


Fig. 5. The assignment of STPs and GGSs.

ID of STP	No. of Vehicle	Route
3	1	11 →3→1
1	2	2→8→6
1	3	15→14→7
3	4	10→12→4→9→13→5

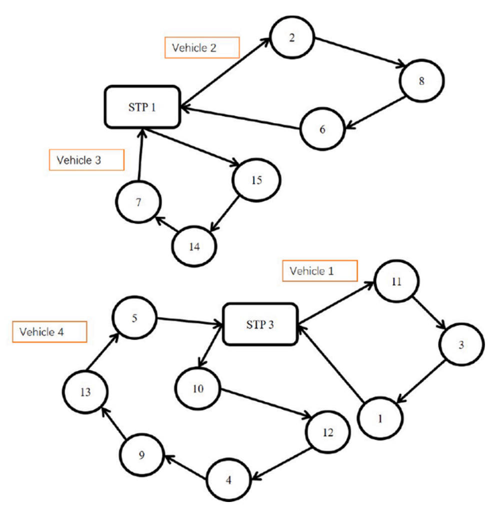


Fig. 6. The visiting order for each GGS.

obtained by Algorithm 3, which will be described later. The constraints (3) ensure that each GGS belongs to one and only one route and that each GGS has only one predecessor in the circuit. Capacity constraints with fuzzy variables of vehicles and STP are satisfied by inequalities (4) and (9) respectively. The constraints (5) and (6) ensure the continuity of each route and the return to the original STP. Constraints (7) are the sub-tours elimination constraints. Constraints (8) specify that a client can be assigned to a repository only if a route linking them is open. Typically, (10) describes the constraints of stochastic travel time, which is adapted from Zhang et al. [42]. Finally, the constraints (11)–(13) state the binary nature of the decision variables.

As described above, constraints (4), (9), and (10) belong to the chance-constraints, which could not be applied to the solving approach directly. So, in the following two sections, we will transfer these constraints to the crisp equations [41].

```
input: a solution (sol) that composed the information of STPs and routes assignments.
initialization: m, n, k, segments; vehicleIndex=0;// the index of a vehicle
customerID=0; // the index of a customer
for i =1:n do
    if(sizeOf(sol[i])!=0)// if the i th STP is not closed
    for j=1:sizeOf(sol[i]) do
        segments[2][vehicleIndex]←i;
        for h=1:sizeOf(sol[i].route) do
            segments[0][customerID]← vehicleIndex;
            segments[1][customerID]←sol[i].route[h];
            customerID++;
        end
        vehicleIndex++;
    end
end
Output: segments.
```

Algorithm 1. Encoding process: from a solution to a chromosome.

```
Input: a chromosome composed by three segments, named segments[0], segments[1] and segments[2].
Initialization: paths=null; sol=null; vehicleSet=unique(segments[0]).// unique is a function to get the unique
    elements in the array
for i= 1:sizeOf(segments[1]) do
    for j= 1:sizeOf(vehicleSet) do
    end
    if segments[0][segments[1][i]]==j then
        paths[j].add(segments[1][i]); // the node is added to the route with jth vehicle
    end
end
for i =1: sizeOf(STPSet) do
    for j =1: sizeOf(segments[2]) do
        if segments[2][j]==i then
            sol[i].add(paths[j]);
        end
    end
end
Output: The solution.
```

Algorithm 2. Decoding process: from a chromosome to a solution.

```
for i from 1 to M do
    for each GGS do
        a ← 1, and u ← 0;
        while a > u do
            (1) randomly generate a real number x in the interval between the left and right boundaries of the triangular
                fuzzy number representing AGS of the GGS, and compute its membership u;
            (2) generate a random number a, a ∈ [0, 1];
            (3) compare a with u, if a ≤ u, then "actual" AGS at the GGS is adopted as being equal to x.
        end
    end
end
(4) Move along the route designed by memetic algorithm, calculate the TC, AC, PC due to route failures in terms of the
    "actual" AGS.
Output: Compute AC which is the average value of additional distances obtained by M times simulation.
```

Algorithm 3. Stochastic simulation.

3.3. Description of fuzzy chance constraints

In the deterministic model, it is straightforward to describe the capacity constraints: the total AGS of the whole route should not exceed the vehicle capacity. However, in the RLRPFSSTT, the capacity constraints become more complex than the deterministic ones. Now, we have to consider the relationship between the fuzzy AGS and the capacity of the vehicles [43].

Indeed, in the planning stage, after serving the jth GGS, the remaining capacity (RC) also becomes a fuzzy variable named $\widetilde{RC_j}$, where

$$\widetilde{RC_j} = VC - \sum_{i=1}^{j} \widetilde{d}_i = \left(VC - \sum_{i=1}^{j} d_{3,i}, q - \sum_{i=1}^{j} d_{2,i}, VC - \sum_{i=1}^{j} d_{1,i} \right) = \left(RC_{1,j}, RC_{2,j}, RC_{3,j} \right).$$

In the deterministic model, if the remaining capacity of the vehicle is higher than the GGS's AGS, this vehicle has the full chance to serve this GGS. However, when dealing with a fuzzy variable of AGS and remaining capacity, how can we decide whether the vehicle should continue visiting the $(j+1)$th GGS or go to the STP directly? Fuzzy credibility theory plays a crucial role to measure the relationship between the AGS of $(j+1)$th GGS and RC, which can be calculated by Eqs. (15) and (16).

$$\mathrm{Cr} = \mathrm{Cr}\{\widetilde{d}_{j+1} \le \widetilde{RC_j}\} = \mathrm{Cr}\{\left(d_{1,j+1} - RC_{3,j}, d_{2,j+1} - RC_{2,k}, d_{3,k+1} - RC_{1,j}\right) \le 0\} \tag{15}$$

$$\mathrm{Cr} = \mathrm{Cr}\{\widetilde{d}_{j+1} \le \widetilde{RC_j}\} = \begin{cases} 0, & d_{1,j+1} \ge RC_{3,j} \\ \dfrac{RC_{3,j} - d_{1,j+1}}{2\left(RC_{3,j} - d_{1,j+1} + d_{2,j+1} - RC_{2,j}\right)}, & d_{1,j+1} \le RC_{3,j}, d_{2,j+1} \ge RC_{2,j} \\ \dfrac{d_{3,j+1} - RC_{1,j} - 2\left(d_{2,j+1} - RC_{2,j}\right)}{2\left(RC_{2,j} - d_{2,j+1} + d_{3,j+1} - RC_{1,j}\right)}, & d_{2,j+1} \le p_{2,j}, d_{3,j+1} \ge RC_{1,j} \\ 1 & d_{3,j+1} \le RC_{1,j} \end{cases} \tag{16}$$

According to our common sense, if RC is very high, and AGS of the next GGS is very low, the next GGS's in this route tends to have more chance to get the service from the current vehicle. (16) shows the credibility $Cr \in [0, 1]$ to measure the event that RC is greater than AGS of next GGS on the current route. When $Cr = 0$, we declare that the vehicle does not have enough RC to serve the next GGS and it should terminate service at the current GGS and return to the STP to unload sewage. When $Cr = 1$, we can be completely sure that the vehicle should serve the next GGS due to enough RC. However, the difficulty is that, in most cases, Cr is neither 0 nor 1, but $Cr \in (0, 1)$. Dispatchers must make a trade-off between risk and cost according to their working experience.

To describe the trade-off, let us introduce the dispatcher preference index DPI, where $DPI \in [0, 1]$. Note that DPI expresses the dispatcher's attitude toward risk. When the dispatcher is not a risk-averse, he/she will choose lower values of parameter DPI. This scenario indicates that the dispatcher prefers to make full use of the available vehicle capacity, although there is an increase in the number of situations, in which the vehicle arrives at the next GGS and is not able to carry out planned service due to small RC. On the other hand, when the dispatcher is a risk-averse, he will choose greater DPI, this may result in less complete utilization of vehicle capacity along the planned routes and less additional distance to cover due to failures [43].

Similarity, in constraints (9), if the STP's RC for serving GGSs is high and the AGS at the next GGS is low, then the STP's chance of loading the

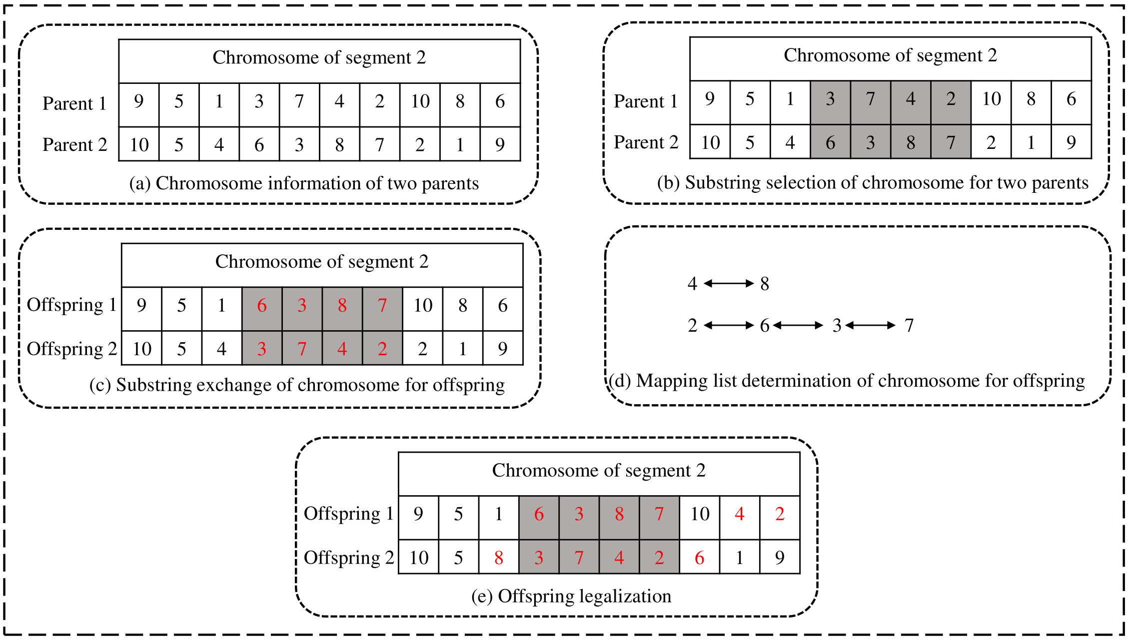


Fig. 7. Partially mapped crossover of MA: An example.

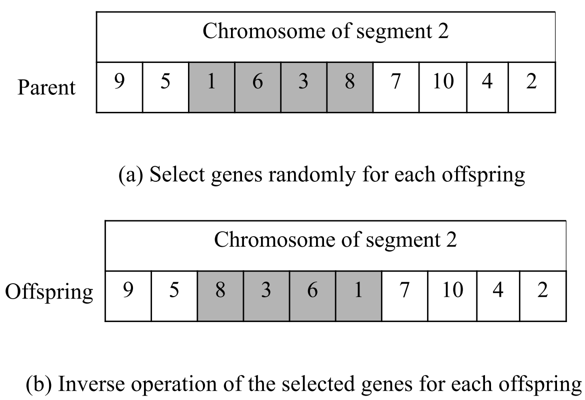


Fig. 8. An example of reverse mutation on segment 2 of the chromosome .

next GGS becomes greater. Here we rename a parameter Assignment Preference Index (API) to describe the risk. Here to guarantee the production, we order $API = 1$, which means the capacity of STP should be satisfied even if all the AGS are very high.

3.4. Transformation of fuzzy chance constraints

Theorem 2. *Based on the crisp equivalent and Theorem 1 (please refer to Theorem 1 in the supplementary material), we transfer the fuzzy chance constraint to the crisp equivalent.*

$$\begin{cases} (1-2*DPI)\sum_{j\in N}\sum_{i\in N_0} d_{j,1}x_{ijk} + 2*DPI*\sum_{j\in N}\sum_{i\in N_0} d_{j,2}x_{ijk} - VC_k \le 0; & 1/2 \le DPI \le 1 \\ (2-2*DPI)\sum_{j\in N}\sum_{i\in N_0} d_{j,2}x_{ijk} + (2*DPI-1)\sum_{j\in N}\sum_{i\in N_0} d_{j,3}x_{ijk} - VC_k \le 0; & 0 \le DPI \le 1/2 \end{cases} \tag{17}$$

Proof. According the Theorem 1, let $\xi_k = d_k, h_k(x) = y_{ik}, y_{ik} \in$ Binary; so, we can get $h_k^{\dagger}(x) = h_k(x) \vee 0 = h_k(x) = y_{ij}, h_k^{-}(x) = -h_k(x) \vee 0 = h_k(x) = 0$, and finally we derive it to the Theorem 2.□

Theorem 3. *Based on the crisp equivalent and Theorem 1 (in the appendix), we can transfer the fuzzy chance constraint of capacity of STP to the crisp equivalent.*

$$\begin{cases} (1-2*API)\sum_{j\in N} d_{j,1}z_{ij} + 2*API*\sum_{j\in N} d_{j,2}z_{ij} - SC_i y_i \le 0; & 1/2 \le DPI \le 1 \\ (2-2*API)\sum_{j\in N} d_{j,2}z_{ij} + (2*API-1)\sum_{j\in N} d_{j,3}z_{ij} - SC_i y_i \le 0; & 0 \le API \le 1/2 \end{cases} \tag{18}$$

Proof. The process of the proof is similar with Theorem 2.□

The constrains (4) and (9) can be replaced by formulations (17) and (18)

3.5. Uncertainty of travel time

As mentioned before, the travel time on each arc is assumed to be independent and to satisfy to the normal distribution indicated by $N(t_{ijk}, \sigma_{ijk})$, where v_{ijk} is the average speed of the of vehicle k on arc (i,j), and σ_{ijk} is the corresponding standard deviation [42].

The left part of the chance constraint (10) of the travel time for each vehicle k can be written as follows.

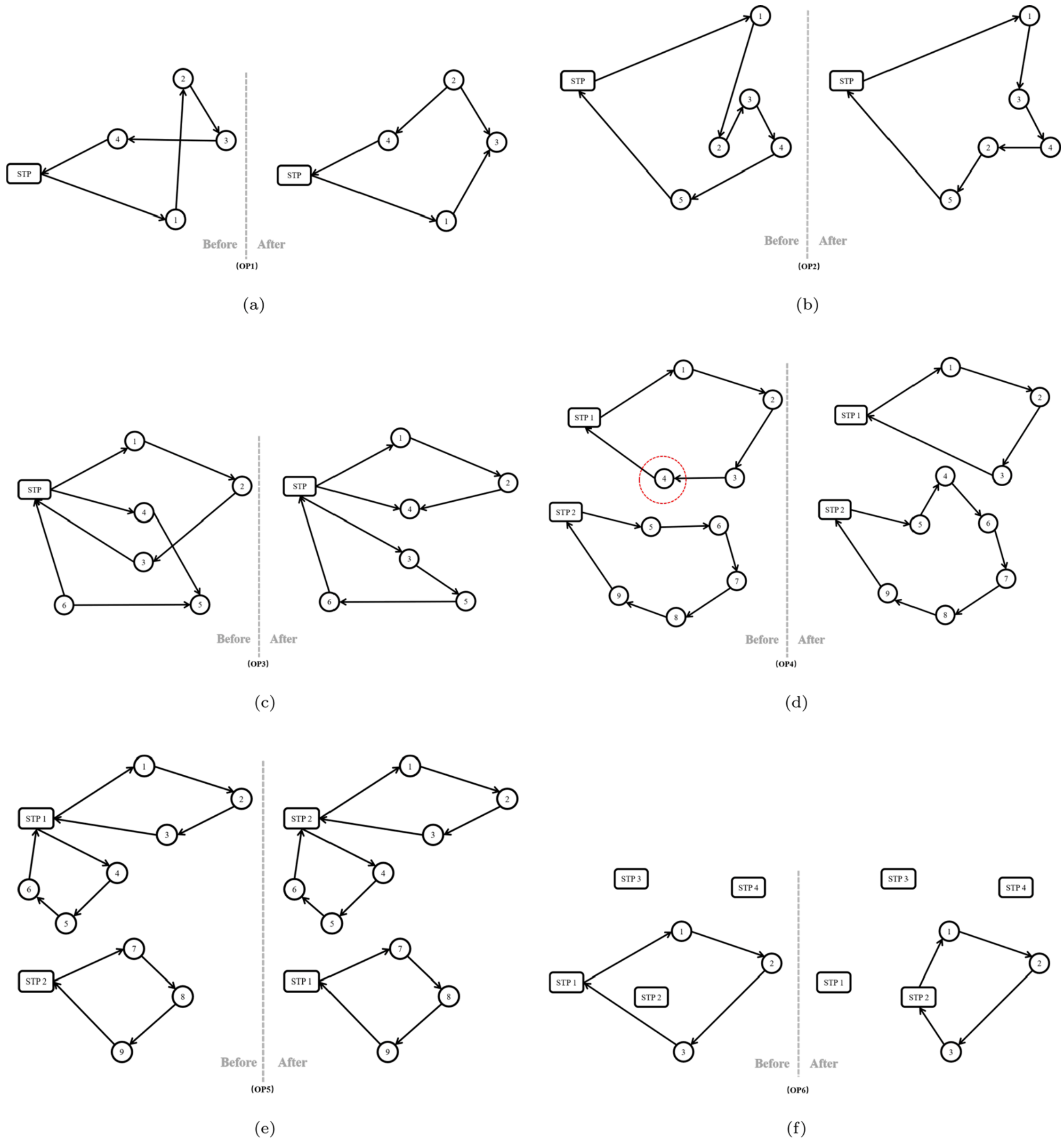


Fig. 9. the procedures of each local search operator .

$$\sum_{i\in N_0}\sum_{j\in N_0} t^{\xi}_{ijk} x_{ijk} - B_k \sim N\left(\sum_{i\in N_0}\sum_{j\in N_0}\left(c_{ij} \Big/ wv_{ijk} + TL_i\right) x_{ijk} - B_k, \sum_{i\in N_0}\sum_{j\in N_0} \sigma^2_{ijk} x^2_{ijk}\right) \tag{19}$$

$$P\left(\eta \le -\frac{\sum_{i\in N_0}\sum_{j\in N_0}\left(c_{ij}/wv_{ijk} + TL_i\right)x_{ijk} - B_k}{\sqrt{\sum_{i\in N_0}\sum_{j\in N_0}\sigma^2_{ijk}x^2_{ijk}}}\right) \ge \alpha \tag{20}$$

We can rewrite this formulation into the following one.

$$\phi^{-1}(\alpha) \le -\frac{\sum_{i\in N_0}\sum_{j\in N_0}\left(c_{ij}/wv_{ijk} + TL_i\right)x_{ijk} - B_k}{\sqrt{\sum_{i\in N_0}\sum_{j\in N_0}\sigma^2_{ijk}x^2_{ijk}}} \tag{21}$$

4. Memetic algorithm

The problem considered in this study is a combination of facility relocation problem and vehicle routing problem. Therefore, the issue is more complicated, and it is an NP-hard problem. Exact methods, such as branch and price, cannot obtain the optimal solution in an acceptable time, especially for massive case problems. Therefore, we consider the meta-heuristic algorithm to solve our problem. MA is one of the most efficient population-based algorithm since it combines with both intensification and diversification strategy, which has been used to solve many combinatorial problems [44]. In this study, the main idea of the memetic algorithm is the hybridization of a genetic algorithm with a local search operator.

4.1. Population initialization

As an individual is a solution, a population in an arbitrary generation is a set of solutions. Maintaining the diversity of the population is a very significant criterion to the convergence of MA. In this study, to avoid the premature convergence of MA, two different population initialization algorithms, including greedy algorithms and random algorithms are proposed. If the entire population is initialized by the same greedy algorithm, it will lead to the population containing similar solutions and very low diversity.

The initial solution is generated by three steps, which are shown in

```
input: a solution (sol);
Generate a random integer number r ∈ [0, 5];
if r == 0 then
    new_sol ← op1(sol);
else if r == 1 then
    new_sol ← op2(sol);
else if r == 2 then
    new_sol ← op3(sol);
else if r == 3 then
    new_sol ← op4(sol);
else if r == 4 then
    new_sol ← op5(sol);
else if r == 5 then
    new_sol ← op6(sol);
end
if z(new_sol) < z(sol) then
    sol ← new_sol // z(·) is the objective function.
end
output: sol.
```

Algorithm 4. The pseudo of local search operators .

Fig. 2(a)–(d). The original map is displayed in Fig. 2(a).

Firstly, a random seed is selected, and then inserted to the current route by selecting the nearest GGS. Once the newly inserted GGS (for example, i) exceeds the capacity of the current route, i will be used as a new seed to construct a new route. The insertion will be continuously performed until all the GGS are inserted into the route. Each route can be thought of as a cluster.

Secondly, for each route, the arithmetic mean of the route center (also called the class center) is obtained by calculating the arithmetic mean of the coordinates.

Finally, the open warehouse is allocated according to the distance between the center of the route and the distance between the STPs and the capacity of the STPs. Specifically, this step can be divided into two strategies.

Strategy (1), randomly select a route as a seed, pick the nearest STP, then assign the closest routes to the STP until the STP capacity is exceeded. The strategy uses the route as the seed to choose to open the nearest STP and then allocates the adjacent route to the STP in turn until all the routes are allocated.

Strategy (2) tends to open up STPs with large capacity and then allocates routes according to the nearest neighbor principle. This strategy will allow reducing the number of open STPs.

4.2. Chromosome design

The proper representation for a chromosome which should satisfy three principles: non-redundancy, soundness and completeness, plays a significant role in the development of MA. In this study, inspired from the work of Zhao et al. [45], a solution includes three parts: (1) opened STPs; (2) vehicles assigned to each opened STP and (3) the route information for each vehicle. Hence, we divide the chromosome into three segments and the chromosome design shows in Fig. 3. Now suppose that there are m gas gathering stations, an opened sewage treatment plant and n-1 candidate STPs to construct sewage treatment plant, respectively. Assume that we now have k homogeneous vehicles. In Fig. 3, the first segment represents the GGS information and each bit corresponds to a GGS. The value in each bit of the first segment represents a specified vehicle serviced to the gas gathering station.

The second segment represents the sequence of GGS. The last segment represents the information of vehicles assigned to STPs. The value in each bit in the last segment represents the STP that the vehicle serviced. Considering the particularity of the model in this study: that point O must be selected, and at least one vehicle and one GGS are served by the STP. In this paper, we design a reasonable chromosome structure.

In order to describe the decoding process in more detail [45], a specific and small size example is given, assuming that $m = 15$, $n = 3$, and $k = 4$, which is shown in Fig. 4.

Fig. 5 shows the GGSs serviced by each vehicle, which can be derived from the segment 1 of Fig. 4.

By using the information from Fig. 5, we can derive the values of indexes shown in segment 2 of Fig. 4. Finally, we can obtain the routes of each vehicle by using the genes and index information in segment 2. The final vehicle routes are shown in Fig. 6.

In this study, the solution is represented with a list that contains the information about routes and STPs. Encoding is the process of converting a solution into a chromosome. The main procedures of the encoding process are shown in Algorithm 1.

As an inverse process, decoding is the process of converting a chromosome into a solution. The pseudo of decoding is shown in Algorithm 2.

4.3. Fitness evaluation

The goal of this study is to minimize the total costs. Hence, the fitness function takes the reciprocal of the objective function.When the

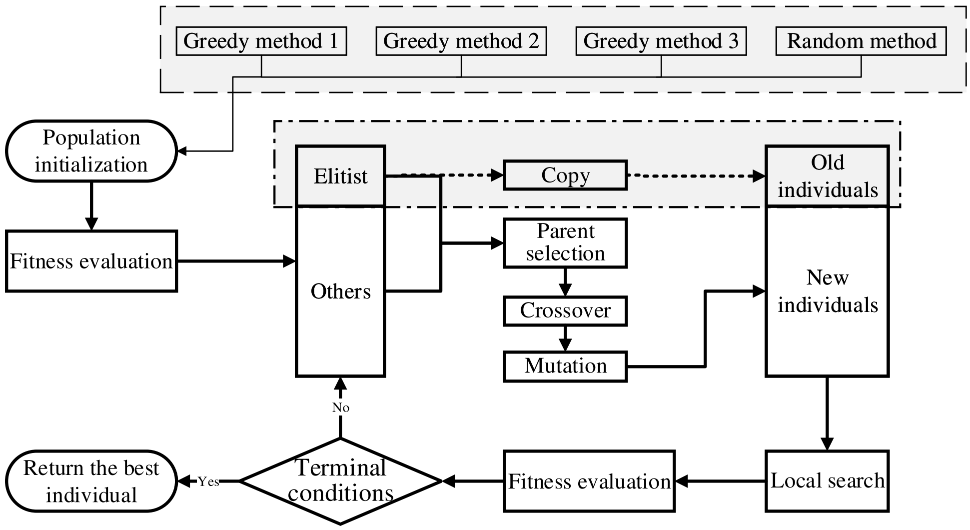


Fig. 10. Conceptual framework of the proposed MA.

Table 3
Parameters for our model and experiments.

Algorithm	Parameters	Values
Mathematical Model	w: the average price for each unit distance	1
	v_{ijk} : the average traveling speed during arc (i,j)	30 unit/min
	B_k : the due time for each vehicle k	480 min
	TL_i: the loading time in GGS i	30 min
	$\widetilde{d}_i$: the fuzzy AGS of GGS i (represented by the nominal AGS d_i)	$[0.8d_i, d_i, 1.2d_i]$
	α: the confidential value in stochastic travel time constraint	0.8
	σ_{ijk}: the stand deviation of travel time between arc i,j in vehicle k	$0.2 * t_{ijk}$
Memetic Algorithm	*popsize*: the number of individuals in the population.	50
	maxgen: the max iteration of the MA.	50× size of the instance.
	rand_ratio: the percentage of the randomly generated individuals in the initial population.	90%
	pe: the percentage of elite in the current population taht will be kept in the offspring.	0.05
	pc: the percentage of individuals selected to take part in crossover.	0.8
	pm: the percentage of individuals selected to take part in mutation.	0.07
	pl: the percentage of individuals selected to take part in local search.	1
stochastic Simulation	M: the times for stochastic simulation	500

chromosome violates any of the constraints in the model, the objective function adds a large enough value M; otherwise, the objective function remains unchanged. In the continuous iterative process, by reducing the value of the fitness function, the individual who violates the constraint condition and the probability of inheriting it to the next generation is significantly reduced, thereby continuously increasing the number of feasible solutions in the population. The detailed steps of stochastic simulation [43] are described in Algorithm 3.

4.4. Main operators

Selection In this study, we mainly consider the elite retention strategy and the roulette method, which are also adopted by Podlena and Hendtlass [46]. First, the elite retention strategy is applied, the individuals with the highest fitness do not participate in the cross mutation and directly pass to the next generation. Then the remainder of the populations will be applied parents selection operation by using the roulette wheel method.

Crossover Crossover operation is a significant operation in MA to generate new gene information. Due to the special structure of chromosome which shows in Fig. 3, we apply different crossover operation methods for each segment of the chromosome. The encoding method of segment 1 and segment 3 are similar; hence they can apply the same crossover operation. The two-point intersections and the partially mapped crossover are adopted for segment 1, 3 and segment 2, respectively [47].

The two-point intersection is widespread and popular crossover operation used in the evolutionary algorithms. Here we omit the explanations of the two-point intersection. Detailed information about two-point intersection can be found in Fu [48].

The partially mapped crossover consists of four steps including sub-string selection, sub-string exchange, mapping list determination and offspring legalization. Here we give an example to illustrate the four steps of partially mapped crossover operation. Fig. 7(a) shows the chromosomes of two parents. First two sub-strings are randomly selected (Fig. 7(b)). Then, the two sub-strings are exchanged (Fig. 7(c)). According to the mapping relationship between the gene of two offsprings, two mapping lists are determined as shown in Fig. 7(d). Finally, the chromosomes of two offspring are legalized with the mapping relationship (Fig. 7(e)).

Mutation Mutation strategy plays a significant role in enhancing the global searching ability and getting rid of local optimal. In this study, two different mutation operation strategies, including swap mutation and reverse mutation, are adopted for segments 1, 3, and segment 2 of the chromosome, respectively. In swap mutation, first, two positions on segments 1 and 3 of the chromosome are randomly selected, respectively. Then the values on segments 1 and 3 of the chromosome are interexchanged. Fig. 8 shows an example of a reverse mutation in segment 2 of the chromosome, which helps us understand how we can generate an offspring. First, we select genes randomly in the parent. The randomly selection of subset genes is shown in Figure8 (a). Then we invert the entire genes in the subset, and the offspring is shown in Fig. 8(b).

Local search As discussed by Decerle et al. [49], the local search strategies could be regarded as a learning stage for improving an individual. The local search operator aims to find a local optimal solution on the basis of the current individual, and it plays an essential role in improving individuals and boosting convergence in MA. In this section, considering the structure of the solution, we have designed six operators, which have comprehensive considerations in the searching space.

Table 4
Comparison with the LRP benchmarks.

instance ID	LB	GRASP					MA							
		Cost	nb_depot	nb_vehicle	cd	cr	Obj	nb_depot	nb_vehicle	cd	cr	computing time (s)	gap1 (MA VS LB)	gap2 (MA VS GRASP)
20-5-1a	54,793	55,131	3	5	25,549	29,582	54,793	3	5	25,549	29,244	8.181	0.00%	− 0.61%
20-5-1b	39,104	39,104	2	3	15,497	23,607	39,104	2	3	15,497	23,607	7.046	0.00%	0.00%
20-5-2a	48,908	48,908	3	5	24,196	24,712	48,908	3	5	24,196	24,712	6.424	0.00%	0.00%
20-5-2b	37,542	37,542	2	3	13,911	23,631	37,542	2	3	13,911	24,951	5.832	0.00%	0.00%
50-5-1	87109.64	90,160	3	12	25,442	64,718	90,111	3	12	25,442	64,669	64.019	3.45%	− 0.05%
50-5-1b	61595.22	63,256	2	6	15,385	47,871	65,461	2	6	15,385	50,076	46.043	6.28%	3.49%
50-5-2	86055.01	88,715	3	12	29,319	59,396	90,495	3	12	32,714	57,781	58.898	5.16%	2.01%
50-5-2b	65787.75	67,698	3	6	29,319	38,379	70,334	3	6	32,714	37,620	42.924	6.91%	3.89%
50-5-2bis	83,439	84,181	3	12	19,785	64,396	84,423	3	12	19,785	64,638	59.35	1.18%	0.29%
50-5-2bbis	51,822	51,992	3	6	18,763	33,229	52,105	3	6	18,763	33,342	40.481	0.55%	0.22%
50-5-3	84075.08	86,203	2	12	18,961	67,242	86,203	2	12	18,961	67,242	69.867	2.53%	0.00%
50-5-3b	61607.4	61,830	2	6	18,961	42,869	63,096	2	6	10,711	52,385	40.332	2.42%	2.05%
100-5-1	272082.37	277,935	3	24	132,890	145,045	283,840	3	24	132,890	150,950	333.635	4.32%	2.12%
100-5-1b	207037.38	214,885	3	11	132,890	81,995	222,271	3	11	132,890	89,381	169.215	7.36%	3.44%
100-5-2	186916.59	196,545	2	24	102,246	94,299	198,113	2	25	102,246	95,867	445.558	5.99%	0.80%
100-5-2b	153827.05	157,792	2	11	102,246	55,546	164,618	2	12	102,246	62,372	173.035	7.01%	4.33%
100-5-3	194202.03	201,952	2	24	88,287	113,665	204,375	2	25	88,287	116,088	417.571	5.24%	1.20%
100-5-3b	149985.58	154,709	2	12	88,287	66,422	163,908	2	11	88,287	75,621	174.676	9.28%	5.95%
100-10-1	258242.64	291,887	3	26	154,942	136,945	321,836	4	25	196,308	125,528	307.649	24.63%	10.26%
100-10-1b	218825.96	235,532	3	12	154,942	80,590	276,836	4	12	196,308	80,528	177.236	26.51%	17.54%
100-10-2	226904.99	246,708	3	24	145,956	100,752	246,579	3	24	145,956	100,623	314.529	8.67%	− 0.05%
100-10-2b	194627.72	204,435	3	11	145,956	58,479	217,366	3	12	149,940	67,426	169.91	11.68%	6.33%
100-10-3	222353.23	258,656	3	25	139,411	119,245	256,629	3	24	139,411	117,218	326.805	15.42%	− 0.78%
100-10-3b	189308.5	205,883	3	11	139,411	66,472	210,757	3	11	139,411	71,346	169.555		2.37%
200-10-1	–	481,676	3	47	253,840	227,836	497,001	3	48	253,840	243,161	1629.152	–	3.18%
200-10-1b	–	380,613	3	22	253,840	126,773	437,505	3	23	236,209	201,296	599.107	–	14.95%
200-10-2	–	453,353	3	48	280,370	172,983	470,034	3	47	280,370	189,664	1339.867	–	3.68%
200-10-2b	–	377,351	3	23	280,370	96,981	392,187	3	23	280,370	111,817	624.029	–	3.93%
200-10-3	–	476,684	3	47	272,528	204,156	485,869	3	46	234,660	251,209	1307.321	–	1.93%
200-10-3b	–	365,250	3	22	234,660	130,590	391,085	3	22	234,660	156,425	607.811	–	7.07%

Note: nb_vehicle:number of vehicles; nb_depot:number of depots; cd: cost of depots; cr: cost of routes.

Table 5
Average simulation results with different *DPI* values for the instance named URLRP020-5-1.

Instance ID	DPI	TC	AC	nb_depot	nb_vehicle	cd	cr(PC)	Total routes	computing time (s)
URLRP20-5-1	0.0	90276.54	13,335.96	4	4	31,999	45,281	58,616.96	53.814
	0.1	89324.64	7,098.90	3	5	25,908	56,836	63,934.90	119.332
	0.2	81639.52	2,219.12	3	5	25,908	53,748	55,967.12	171.336
	0.3	81894.56	3,553.00	3	5	25,908	53,149	56,702.00	221.147
	0.4	77509.64	542.46	3	5	25,908	51,240	51,782.46	274.729
	0.5	74573.56	250.48	3	5	25,908	48,633	48,883.48	326.732
	0.6	78037.76	443.44	3	5	25,908	52,036	52,479.44	377.438
	0.7	85,681	0.00	3	6	25,908	59,773	59,773.00	439.714
	0.8	79,433	0.00	3	6	25,908	53,525	53,525.00	545.937
	0.9	81,515	0.00	3	6	25,908	55,607	55,607.00	667.707
	1.0	79,497	0.00	3	7	25,908	53,589	53,589.00	766.437

Note: nb_vehicle:number of vehicles; nb_depot:number of depots (STPs); cd: cost of depots (STPs); cr: cost of routes; TC: total cost; AC: additional cost; PC: planned cost.

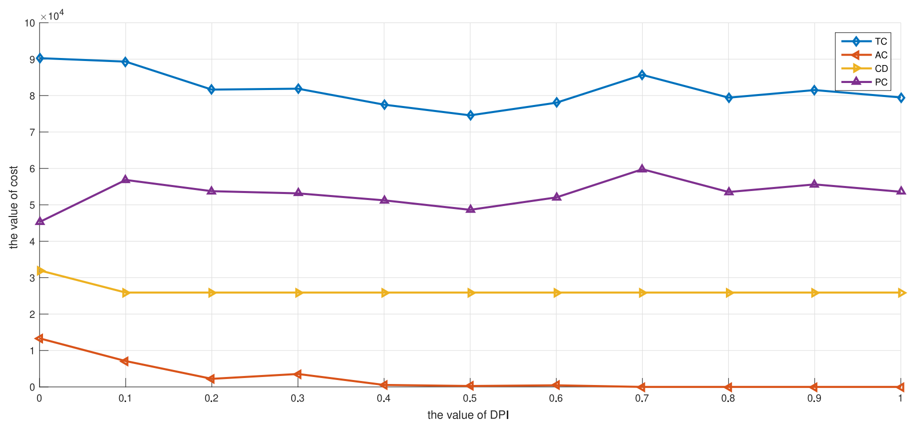


Fig. 11. The costs change tendencies with different *DPI* values .

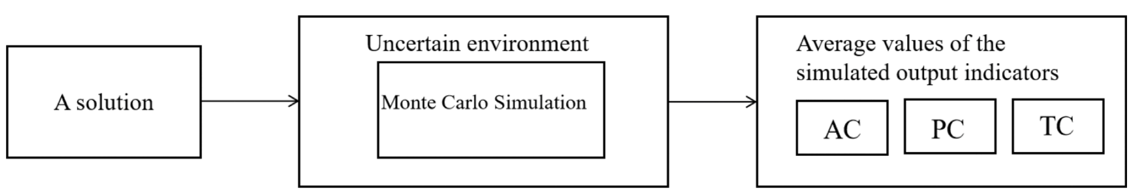


Fig. 12. Evaluating procedures of each solution in an uncertain environment.

The introduction of the operators is described as follows, and they are depicted in Fig. 9.

(op1) intra-route- swap: two GGSs are randomly selected, and their positions are swapped.
(op2) intra-route-reverse: two GGSs are randomly selected, then all the arcs along the two vertices are reversed.
(op3) inter-route-opt: two GGSs in different routes are selected, then their places are swapped.
(op4) inter-route-insert: a GGS, and also a route excluding this GGS are randomly selected, then the GGS is inserted to the best position of the selected route.
(op5) inter-STP-opt: two STPs are randomly chosen, then the two STPs are swapped.
(op6) inter-STP-insert: one STP is selected, and another un-enabled STP replaces the current STP.

Generally, the six operators could be divided into three categories, namely (op1) and (op2) can be viewed as the improvement of a single route, while (op3) and (op4) are regarded to optimize the assignment of GGSs and vehicles. Finally, (op5) and (op6) are performed at the location stage. What should be highlighted here is that, in the local search, (op4) can help reduce the number of used vehicles and reduce the number of opened STPs.

As presented above, each operator has a different role in exploring the solution space and finding a new solution. Considering that performing all the operators for a single individual in one generation may be time-consuming, we choose to perform one operator in one generation each time. All the operators are selected randomly but with the same probability and the pseudo is shown in Algorithm 4. We find that the complexity of the local search algorithm is $O(n^2)$.

4.5. Framework of the proposed MA

We summarize the conceptual framework of the proposed MA as follows.

Step (1): Initialize the population with three greedy methods and random method, then evaluate all the individuals.
Step (2): Move the elitist individuals to the next generation.
Step (3): Apply parents selection and crossover operation to generate new offsprings.
Step (4): Do mutation operation for all the individuals with the mutation probability.

Table 6
Comparison between deterministic AGS and fuzzy AGS models.

InstanceID	Deterministic demand model						Fuzzy demand model						
	TC	AC	nb_depot	nb_vehicle	cd	cr	TC	AC	nb_depot	nb_vehicle	cd	cr	computing time (s)
URLRP20-5-1	74897.03	329.8	3	5	25,908	48,989	83,107	0.00	3	6	25,908	57,199	85.74
URLRP20-5-1b	57771.00.0	0	2	3	25,076	32,695	60,742	0.00	2	3	25,076	35,666	64.556
URLRP20-5-2	64866.03	336.38	3	5	24,196	40,670	69,254	0.00	3	6	24,196	45,058	47.231
URLRP20-5-2b	49361.01	116.7	2	3	21,619	27,742	57,661	0.00	2	3	21,619	36,042	47.716
URLRP50-5-1	153009.02	1985	2	13	20,100	132,909	158,849	0.00	2	14	20,100	138,749	223.553
URLRP50-5-1b	105635.04	391.96	2	6	20,100	85,535	112,562	0.00	2	6	20,100	92,462	238.247
URLRP50-5-2	154914.07	697.8	3	13	36,094	118,820	164,691	0.00	3	15	36,094	128,597	224.297
URLRP50-5-2BIS	145178.02	1757.72	3	13	19,816	125,362	163,040	0.00	3	14	19,816	143,224	224.121
URLRP50-5-2b	114571.00	0	3	6	36,094	78,477	130,433	0.00	3	7	36,094	94,339	287.327
URLRP50-5-2bBIS	92944.08	754.9	3	6	19,242	73,702	95,440	0.00	3	7	19,242	76,198	269.216
URLRP50-5-3	134526.01	1250.5	3	12	24,173	110,353	144,400	0.00	2	14	19,045	125,355	221.724
URLRP50-5-3b	105989.02	17	3	6	24,173	81,816	111,257	0.00	3	6	24,173	87,084	280.4
average:	108,717.30	636.48	2.67	7.58	24,715.92	79,755.83	112,619.67	0.00	2.58	8.42	24,288.58	88,331.08	184.51

Note: nb_vehicle:number of vehicles; nb_depot:number of depots (STPs); cd: cost of depots (STPs); cr: cost of routes, TC: total cost; AC: additional cost; PC: planned cost.

Step (5): Apply local search to the newly generated offsprings.
Step (6): Calculate the fitness value for all the individuals.
Step (7): If the stop conditions are met, return the best solution otherwise go to Step (2).

Fig. 10 shows the conceptual framework of the proposed MA.

5. Experimental results

In the above sections, we have formulated a model named RLRPFSSTT and proposed a memetic algorithm based heuristic to solve the problem. This section mainly reports and analyzes some of the experimental results. As mentioned, the RLRPFSSTT is not only a feature of combinatorial optimization, but also belongs to uncertain optimization. So, the classical commercial solvers like CPLEX, or GUROBI could not solve the model directly.

To validate the proposed models and algorithms, we have performed several series of experiments. In this section, firstly, the newly developed instances are presented in Section 5.1, then Section 5.2 reports the experimental results for the reduced model. Thirdly, the detailed experiments and analysis of the uncertain model are presented in section 6.3, in which the sensitivity analysis of parameters are also performed to guide the policymakers.

5.1. Introduction to the instances

To the best of our knowledge, no standard benchmark instances in the literature are completely suitable for our problem. We generate instances for our problem based on the benchmark instances provided by Prins et al. [9]. The instances generated by Prins et al. [9] are grouped into a few groups according to their scale of customers and depots. Each category has its own characteristic of depots and customers. For each instance, Prins et al. [9] has defined coordinates of the location, demand, the value of capacity, and fixed cost.

In our studied problem, there is an analogy with the instances developed by Prins et al. [9]. Each STP corresponds to one depot, and every GGS is equivalent to a customer. We make no changes to the customers' locations, AGS, and capacity in Prins et al. [9]'s original instances, but we have introduced the following changes to the original data to adapt it to our problem. Firstly, we assume that the first GGS is the original built, and others are new location candidates waiting to be selected. Secondly, we consider a uniform speed between arcs. Thirdly, we have added a new parameter *DPI* to make the trade-off between the risk and full utilization of the vehicles and STPs. To distinguish the difference between our instances and classical instances of Prins et al. [9], we name our instances as "URLRP-a-b-X," in which a is the number of GGS, while b is the number of STP, and X is the specific name of this instance. All the codes are implemented by java in the ubuntu 18.04 system on the laptop with Intel®Core™ i7 Processors and 2.4 GHZ.

The main parameters used in the proposed algorithms and model are listed in Table 3. The tuning of the parameters are obtained by the Design of Experiments[50].

5.2. Comparison with the published results

Because the proposed model is entirely new, and no other researcher has solved these same instances, we could not compare the published works to validate our proposed heuristics. Our problem will be reduced to a classical LRP presented by Prins et al. [9] if we assume the following aspects. (1) The constraints of the fuzzy AGS and stochastic travel times become deterministic. (2) The original set if STP *O* is an empty set; STPs and GGSs are regarded as depots and customers, respectively. To validate the efficiency of our algorithm, we first apply the MA to test the instance of Prins et al. [9].

Table 4 reports the results of MA and GRASP for solving the classical benchmarks. The first column shows the ID of the instance by indicating the size. For example, 20-5-1 discloses that the number of customers is 20, and the amount of given candidates for building depots is 5. The BKS column indicates the best solutions found so far. The LB column has missing values because it is difficult to seek a good lower bound in a limited time when the instances' size becomes greater. We report our results in the final column with MA by comparing them with BKS and Prins et al. [9]. As shown in the last column, we find that for nine instances, the GRASP approach gives better solutions; for two instances, we have the same solutions, and for the remaining instances, our approach is better. We have also made a full comparison with the recent results reported by Lopes et al. [51] and Peng et al. [52]. Please check the detail in the supplementary material.

We would like to emphasize that this article's primary purpose is not to develop the best algorithm to obtain a better algorithm than historical results. Instead, this article summarized a model from a practical problem, and the most exciting part is to develop an effective heuristic algorithm to solve the real-life application. The comparison with the published results is only used to illustrate the proposed MA is effective and acceptable. The proposed MA will be applied to solve the uncertain optimization problem in the next section.

5.3. Results of the uncertain optimization results

5.3.1. Sensitivity analysis

As mentioned before, *DPI* is an essential parameter for helping decision-makers make a reasonable decision. However, the value of *DPI* is unknown in advance, and it is selected by empirical experiments, which can be regarded as sensitivity analysis of *DPI* value. As an example, we have chosen a instance named URLRP20-5-1. In this part, let the value of *DPI* vary within the interval $[0, 1]$ with a step of 0.1, then record the simulation results of the best solutions.

The simulation results for URLRP20-5-1 can be found in Table 5 and Fig. 11. These tables and figures show tendencies regarding the cost caused by the planned distances (PC), additional cost caused by the additional distances due to failures (AC), the cost for total distance (TC), and other indicators that vehicles covered as the dispatcher preference index varies. We observe that with the increase of the *DPI* value, the AC decreases, and there is no clear trend in the TC and PC. For instance URLRP20-5-1, the AC strictly decreases as *DPI* value increases from 0 to 0.6. However, when $DPI \in [0.7, 1]$, the AC becomes 0, and this means that there is no failure route. According to these results, we find that 0.8 is the best *DPI* value to make the decision.

As mentioned in Section 4.2, *DPI* expresses the dispatcher's attitude toward risk. When the dispatcher is not risk-averse, he/she will choose lower values of parameter *DPI*. This scenario indicates that the dispatcher does not prefer risk-averse. When *DPI* is with a high value, the dispatcher prefers risk-averse, which would decrease the chance of generating additional cost due to the failure routes. The simulation results in Table 5 empirically prove this point.

5.3.2. Comparison with deterministic AGS model

As we have discussed, when the *DPI* value is low, the decision-maker subjectively desires to make full use of the vehicle, so the PC is minimal. In this situation, the chance that the vehicles may not meet the GGSs' AGS increases, and the driver has to return to the STP to load more AGS. These failure routes bring more additional distances, leading to the delay of the service time. Higher values of *DPI* are characterized by lower vehicle capacity utilization along the planned routes and less AC due to fewer failures.

To further compare with the deterministic AGS model, we have performed a Monte Carlo Simulation for each solution by assuming it under an uncertain environment. The procedures can be described by Fig. 12, and a detailed algorithm is given in Algorithm 3. Table 6 summarizes the comparison results.

Table 6 reports the simulation results of the solutions obtained by considering the fuzzy AGS and deterministic AGS model. We set the parameter *DPI* as 0.8, which is the best *DPI* value. In these scenarios, AC is equal to 0, which means there is no failure route. However, the solutions obtained by deterministic AGS show a high AC, which discloses that, in this situation, these solutions tend to have more failure routes.

Finally, when comparing the TC, the solution with considering fuzzy AGS is slightly more expensive than without considering fuzzy information. The *t*-test is to use the *t* distribution theory to infer the probability of the difference, so as to compare whether the difference between two averages is significant. We carried out a *t*-test on the values of TC in the group named "deterministic model" and group called "fuzzy model". We find that the *t*-value equals to 0.2455 (greater than 0.05, reject the hypothesis), which indicates that the values of TC has no significant different.

Considering that robustness is one of the most critical issues in gas production, it is still acceptable to pay a slight additional cost. So, we may conclude that the relocation-routing model considering fuzzy AGS is more reasonable to help the policy-makers make reasonable decisions about relocation and vehicle routing problem.

6. Conclusions

Most of the previous studies found in the literature about gas-field logistics systems tend to study the location problem of the facility separately from the vehicle routing problem. Some gas production enterprises failed to predict their production in the early enough, and when the facility (such as STP) could not satisfy high scale of production, the policymakers intend to build some new facilities. The objective of this issue is to minimize the total cost, including fixed cost of the newly built facilities, logistics costs. This article, considering this scenario, proposed a fuzzy chance-constraint for a relocation-routing problem in the area of green production of gas. Fuzzy AGS and stochastic travel time were taking into account in this model. Given that the model has attributes of combinatorial optimization and uncertain programming, we developed a solving approach by integrating MA and Monte Carlo simulation.

To validate the proposed approach, first, the model was reduced to the classical LRP. Then the comparison with Prins et al. [9] and Prins et al. [10] shows that MA is an effective and efficient algorithm for this study. Then MA was applied to solve the fuzzy chance constraints. The AC due to route failures was estimated by Monte Carlo simulation procedures for each planned route. Several different sizes of test instances are then generated, and the computational experiments showed that the dispatcher preference index greatly influenced the planned cost, additional cost, and total cost. Best DPI were obtained from empirically analysis by changing the *DPI* value with a step of 0.1 gradually. Finally, the comparison between the solutions obtained by the fuzzy AGS model and the deterministic AGS model validates the strength of considering fuzzy AGS. The best *DPI* obtained by our model and algorithm can help the decision-makers make a better decision when they trade off the cost and risk.

The location-routing problem is a subject that has been widely studied in the manufacturing industries. But the current related research is aimed at helping companies plan a completely new logistics layout. In developing countries, many companies are facing business expansion. This means that the most primitive logistics layout cannot meet the growing development needs. Therefore, it is necessary to optimize further and add new logistics facilities on the basis of the original logistics facility layout to keep the entire logistics system in an optimal state. Therefore, this research is an essential reference value for making up for the existing deficiencies and providing logistics decision-making for developing enterprises.

The limitation of this paper is that the model does not consider the dynamic changes [53] of AGS and carbon emission of the vehicles [54], which could be the main work of future research. On the other side, some senior techniques will also be nested into meta-heuristic to improve the efficiency of this solving approach.

CRediT authorship contribution statement

Yong Shi: Conceptualization, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Yanjie Zhou:** Methodology, Visualization, Writing – original draft, Writing – review & editing. **Toufik Boudouh:** Writing – review & editing, Supervision. **Olivier Grunder:** Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.swevo.2022.101129

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